Modulation Recognition for MIMO Communications

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ABSTRACT

A large amount of modulation recognition algorithms has been reported in literature for Single-Input Single-Output (SISO) communications. But, to our knowledge, none of them have dealt with Multiple-Input Multiple-Output (MIMO) communications. The issue addressed in this paper is the modulation recognition for MIMO communications under the assumption of a perfect symbol timing. In the first part of this paper, we develop the optimal solution based on Average Likelihood Ratio Tests. Although this solution is optimal, it requires the knowledge of the propagation channel which is usually unknown in a non cooperative environment. To overcome this problem, in the second part of this paper we propose an alternative solution based on Hybrid Likelihood Ratio Tests. Compared to the ALRT classifier, simulations show that the HLRT classifier presents good performances.

1. INTRODUCTION

Communication signals travelling in space with different modulation types [1]. The task of a modulation recognition algorithm is to blindy identify the modulation type and the signal parameters of an intercepted communication. The blind recognition of digital modulation is important for many applications such as signal interception, interference identification and Communication Intelligence. In literature, different approaches have been proposed to recognize the modulation of a SISO (Single-Input Single-Output) communications from the received signal. The references [2] and [3] present critical reviews of the modulation recognition algorithms for SISO communications.

Other investigations conducted in parallel have been devoted to the development of new technologies aimed at enhancing the reliability of data transmission in wireless communication systems. Among them, one of the most promising relies on the use of multiple antennas (MIMO). MIMO technology has been standardized in IEEE 802.16e, IEEE 802.11n. Currently, the blind modulation recognition for MIMO communications is a research issue poorly addressed in literature. In this paper, we propose two methods to accomplish this task. This paper is organized as follows. Section II presents the signal model and the assumptions. In section III, we develop the optimal solution for the modulation recognition problem based on Average Likelihood Ratio Tests. As this optimal solution is difficult to implement in practise, we present an alternative method based on Hybrid Likelihood Ratio Tests in section IV. Finally the performances of two proposed methods are compared in section V.

2. SIGNAL MODEL AND ASSUMPTIONS

Let us consider a multi-transmitter communication (MIMO) using n_t antennas which is intercepted by a receiver composed of n_r antennas. Let us denote by the column vector $X(k)$ the n_r samples received at time k . Under the assumption of a frequency flat and time invariant channel and under a perfect estimation of the symbol timing, the received samples can be expressed as:

$$X(k) = \mathbf{H}S(k) + B(k) \tag{1}$$

where **H** corresponds to the $n_r \times n_t$ complex channel matrix and $B(k)$ is a column vector of size n_r which corresponds to the additive noise. We assume that the additive noise follows a complex gaussian circular law $\mathcal{N}(0, \sigma^2\mathbf{I}_{n_t})$, where σ^2 corresponds to the noise variance on each receiver and where $\mathbf{I}_{n_r}$ corresponds to the identity matrix of size n_r. The column vector $S(k) = [s_1(k), \cdots, s_{n_t}(k)]^T$ contains i.i.d complex random variables which corresponds to the transmitted signals. We assume normalized constellation, i.e. $E[S(k)S^H(k)] = \mathbf{I}_{n_t}$, and that the gain factor is contained in the channel matrix. Furthermore, we assume that each transmitted signals $s_j(k)$ belong to a linear modulation denoted M_j (PSK, QAM or PAM) which is unknown at the receiver side.

The goal of this paper is to blindly recognize the set of modulation $\mathcal{M} = \{M_1, \cdots, M_{n_t}\}$ of the n_t transmitted signals from N received samples $\mathbf{X} = [X(1) \cdots X(N)]$. The blind modulation recognition can be performed by two kind of classifiers: maximum likelihood or pattern recognition classification methods. In this paper, we adopt the first method which presents better performances [3]. Under the ideal case of a known channel matrix $\mathbf{H}$, we expose the optimal solution based on an Average Likelihood Ratio Tests (ALRT). The main interest of the ALRT is to provide an upper bound on the performances of any method. Then, we propose an alternative method, based on an Hybrid Likelihood Ratio Tests (HLRT), which does not require the knowledge of the channel matrix.

3. ALRT APPROACH FOR A KNOWN CHANNEL MATRIX

In this section, we propose the optimal solution for the modulation recognition of MIMO communications. Within the Likelihood Based framework, the modulation recognition is formulated as a multiple composite hypothesis-testing problem. The recognized modulations $\widehat{\mathcal{M}} = \{\widehat{M}_1, \cdots, \widehat{M}_{n_t}\}$ are the ones which maximize the Likelihood Function (LF) given by:

$$\Lambda^{(1)}(\mathbf{X}|\mathbf{H}, M_1, \cdots, M_{n_t}, \sigma^2) = \text{pr}(\mathbf{X}|\mathbf{H}, M_1, \cdots, M_{n_t}, \sigma^2) \quad (2)$$

As the transmitted symbols are independent, the LF can be expressed as:

$$\Lambda^{(1)}(\mathbf{X}|\mathbf{H}, M_1, \cdots, M_{n_t}, \sigma^2) = \prod_{k=1}^{N} \text{pr}(X(k)|\mathbf{H}, M_1, \cdots, M_{n_t}, \sigma^2) \quad (3)$$

The received samples $X(k)$ depend on the transmitted symbols which are unknown at the receiver side. To threat these unknown quantities, the optimal solution is the ALRT [3]. The ALRT method treats the unknown quantities as a random variables and the LF is computed by averaging over them. Under the assumption that the symbols are spatially independent, we obtain:

$$\Lambda^{(1)}(\mathbf{X}|\mathbf{H}, M_1, \cdots, M_{n_t}, \sigma^2) = \prod_{k=1}^{N} \sum_{i_1=1}^{l_1} \cdots \sum_{i_{n_t}=1}^{l_{n_t}} \text{pr}(X(k)|\mathbf{H}, s_{i_1}^{(1)}, \cdots, s_{i_{n_t}}^{(n_t)}, \sigma^2) \prod_{j=1}^{n_t} \text{pr}(s_{i_j}^{(j)}) \quad (4)$$

where l_j corresponds to the alphabet size of the modulation M_j and where $s_i^{(j)}$ correspond to the symbol transmitted on the j^{th} antenna. For each antenna, the symbols are independent and identically distributed, i.e. $\text{pr}(s_{i_j}^{j}) = \frac{1}{l_j}$. So,

$$\Lambda^{(1)}(\mathbf{X}|\mathbf{H}, M_1, \cdots, M_{n_t}, \sigma^2) = \frac{1}{\left(\prod_{j=1}^{n_t} l_j\right)^N} \prod_{k=1}^{N} \sum_{i_1=1}^{l_1} \cdots \sum_{i_{n_t}=1}^{l_{n_t}} \text{pr}(X(k)|\mathbf{H}, s_{i_1}^{(1)}, \cdots, s_{i_{n_t}}^{(n_t)}, \sigma^2) \quad (5)$$

Let us denote by $S_{i_1,\cdots,i_{n_t}} = [s_{i_1}^{(1)}, \cdots, s_{i_{n_t}}^{(n_t)}]^T$ the column vector of size n_t which corresponds to the transmitted symbols. Using the equation (1) and the fact that the additive noise $B(k)$ follows a complex gaussian circular law $\mathcal{N}(0, \sigma^2\mathbf{I}_{n_t})$, $X(k)$ follows a gaussian circular law $\mathcal{N}(\mathbf{H}S_{i_1,\cdots,i_{n_t}}, \sigma^2\mathbf{I}_{n_t})$. So, the probability of $X(k)$ is given by:

$$\text{pr}(X(k)|\mathbf{H}, s_{i_1}^{(1)}, \cdots, s_{i_{n_t}}^{(n_t)}, \sigma^2) = \frac{1}{\pi^{n_r}\sigma^{2n_r}} \exp\left(-\frac{1}{\sigma^2}||X(k) - \mathbf{H}S_{i_1,\cdots,i_{n_t}}||_F^2\right) \quad (6)$$

where $||.||_F^2$ corresponds to the Frobenius norm. Using equation (6) on equation (5) leads to the expression of the LF:

$$\Lambda^{(1)}(\mathbf{X}|\mathbf{H}, M_1, \cdots, M_{n_t}, \sigma^2) = \frac{1}{\left((\pi\sigma^2)^{n_r} \prod_{j=1}^{n_t} l_j\right)^N} \prod_{k=1}^{N} \sum_{i_1=1}^{l_1} \cdots \sum_{i_{n_t}=1}^{l_{n_t}} \exp\left(-\frac{1}{\sigma^2}||X(k) - \mathbf{H}S_{i_1,\cdots,i_{n_t}}||_F^2\right) \quad (7)$$

Finally, the optimal solution for the MIMO modulation recognition problem is given by the set of n_t modulations $\widehat{\mathcal{M}} = \{\widehat{M}_1, \cdots, \widehat{M}_{n_t}\}$ given by:

$$\widehat{\mathcal{M}} = \arg \max_{M_1,\cdots,M_{n_t}} \left(\Lambda^1(\mathbf{X}|\mathbf{H}, M_1, \cdots, M_{n_t}, \sigma^2)\right) \quad (8)$$

In many environment, the computational complexity and the need for prior knowledge (like the channel matrix $\mathbf{H}$), can render the ALRT impractical. In the following, we propose an alternative approach based on Hybrid Likelihood Ratio Tests (HLRT).

4. HLRT APPROACH FOR AN UNKNOWN CHANNEL MATRIX

This section proposes a second method for the modulation recognition which does not require the knowledge of the channel matrix. The main idea of this method is to break the MIMO communication into n_t SISO communications.

4.1. From MIMO to SISO communications

Under the assumption that the number of receiver antennas is greater or equal to the number transmitter antennas, an Independent Component Analysis (ICA) is applied on the received data $X(k)$ to break the MIMO communication into n_t SISO communications. An ICA algorithm finds a separating matrix of size $n_t \times n_r$, **W**, which maximises the independency of components, $Y(k) = [y_1(k) \ \cdots y_{\widehat{n}_t}(k)]^T$, so that:

$$Y(k) = \mathbf{W}X(n) \tag{9}$$

The reference [4] lists a large number of ICA methods proposed in the literature which can blindly find the matrix **W**. In this paper we keep the JADE algorithm [5] which presents good behaviors for signals far from gaussianity [6]. As the transmitted symbols are independent, the vector $Y(k)$ can be expressed according to the transmitted signals $S(k)$ as (see reference [5]):

$$Y(k) = \mathbf{PD}S(k) + \mathbf{W}B(k) \tag{10}$$

where **P** and **D** denote respectively an unknown permutation matrix and a diagonal matrix of size $n_t \times n_t$. Each independent component $y_u(k)$ $(1 \leq u \leq n_t)$ can be expressed as:

$$y_u(k) = \alpha_u e^{j\theta_u} s_v(k) + b_u(k) \tag{11}$$

where the scalars α_u and θ_u are respectively unknown scale and phase factors. The additive noise $b_u(k)$ follows a gaussian law with zero mean and variance σ_u^2. Using the equation (10) and the fact that $E[B(k)B^H(k)] = \sigma^2 \mathbf{I}_{n_r}$, the variance σ_u^2 is equal to:

$$\sigma_u^2 = \sigma^2 W_u W_u^H \tag{12}$$

where W_u denotes the u^{th} row of the separating matrix **W**. It is important to remark that, due to the permutation matrix **P**, the u^{th} independent component corresponds to the v^{th} transmitted signal (u is not necessary equal to v).

The equation (11) refers to a SISO signal model. The ICA permits us to convert the problem into n_t SISO modulation recognition problems. So after the ICA, we propose to recognize individually the modulation M_v of each independent component $\mathbf{y}_u = [y_u(1), \cdots, y_u(N)]$. Although this approach does not exploit all the information contained on $Y(k)$, it reduces the complexity of the classifier.

4.2. Modulation recognition for SISO communication

Let us focus on the independent component $\mathbf{y}_u$. The modulation $\widehat{M_v}$ recognized is the one which maximizes the likelihood function $\Lambda^{(2)}(\mathbf{y}_u|\alpha_u, \theta_u, M_v, \sigma_u^2)$. The optimal solution is given by the ALRT-LF which is equal to (see reference [7]):

$$\Lambda^{(2)}(\mathbf{y}_u|\alpha_u, \theta_u, M_v, \sigma_u^2) =$$

$$\frac{1}{(\pi l_v \sigma_u^2)^N} \prod_{k=1}^{N} \sum_{i=1}^{l_v} \exp\left(-\frac{|y_u(k) - \alpha_u e^{j\theta_u} s_i^{(v)}|^2}{\sigma_u^2}\right) \tag{13}$$

The computation of the ALRT-LF requires the knowledge of the scale α_u and of the phase θ_u factors which are unknown quantities. To compute the ALRT-LF, we propose to replace the unknown quantities by their estimates. This approach is called an Hybrid Likelihood Ratio Test (HLRT).

The scale factor, α_u, is estimated by Method of Moments (MOM). Using the fact that $E[S(k)^H S(k)] = \mathbf{I}_{n_t}$ and the equation (11), the MOM estimate of the scale factor, $\widehat{\alpha}_u$ is given by;

$$\widehat{\alpha}_u = \sqrt{E[|y_u(k)|^2] - \sigma_u^2} \tag{14}$$

The phase factor, θ_u $(0 \leq \theta_u < 2\pi)$ is estimated by Maximum Likelihood (ML). Finally the modulation $\widehat{M_v}$ recognized is obtained by replacing the unknown quantities by their estimates in the likelihood function, i.e. :

$$\widehat{M_v} = \arg\max_{M_v} \left[\max_{\theta \in [0 \ 2\pi]} \left(\Lambda^{(2)}(\mathbf{y}_u|\widehat{\alpha}_u, \theta, M_v, \sigma_u^2) \right) \right] \tag{15}$$

5. SIMULATION RESULTS

In this section, monte Carlo simulations were run to highlight the performances of the two proposed algorithms for the MIMO modulation recognition. They were aimed at recognizing 4 types of linear modulations: BPSK, QPSK, 16PSK and 16QAM transmitted by a MIMO communication using $n_t = 2$ transmit antennas.

500 Monte Carlo trials were performed for each type of modulation. Moreover, the conditions for each Monte Carlo trial were: i) A Rayleigh distributed channel, which means that each element of **H** follows a complex gaussian circular law with zero mean and unit variance, ii) 512 transmitted symbols on each antenna, iii) The same modulation used by the $n_t = 2$ transmit antennas, iv) a complex gaussian circular and spatially uncorrelated noise, verifying $E[B(k)B^H(k)] = \sigma^2 \mathbf{I}_{n_r}$, and v) a signal to noise ratio (SNR) equals to $10\log(\frac{\sigma_s^2}{\sigma^2})$ with $\sigma_s^2 = \mathrm{tr}(E[S(k)S^H(k)])$ where tr denotes the matrix trace. The performances of the two algorithms were measured in term of probability of correct detection. This probability is approximated by averaging the number of correct detections over the number of trials, modulation, and transmitted signals (total number of simulations $500 \times 4 \times 2$). In the following, we present the probability of correct detection obtained with the ALRT and HLRT classifiers.

5.1. Performances of the ALRT classifier

The ALRT classifier provides an upper bound on the performances of any classifier. The figure 1 presents the probability of correct detection with respect to the signal to noise ratio. It shows that for 1 receiver antenna, the probability of correct detection is close to 1 at SNR=20dB. The confusion matrix reveals that high SNR (20dB) is required to correctly discriminate 16PSK and 16QAM modulations. Increasing the

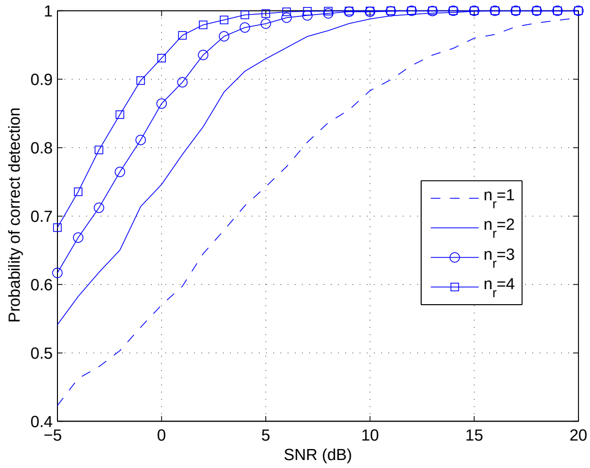

Fig. 1. Performances of the ALRT classifier for the recognition of 4 modulations. The emitter used 2 antennas and transmits 512 symbols on each antenna.

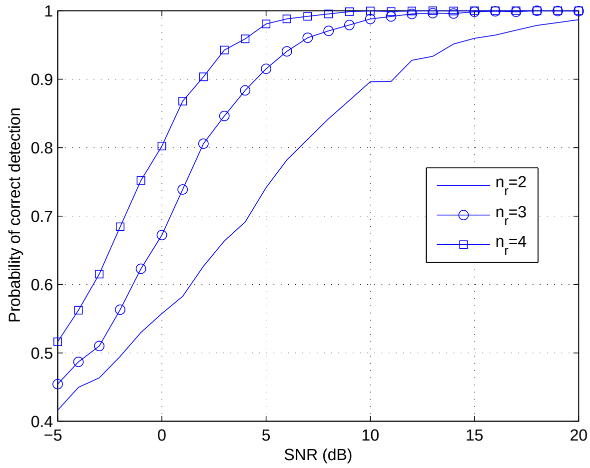

Fig. 2. Performances of the HLRT classifier for the recognition of 4 modulations. The emitter used 2 antennas and transmits 512 symbols on each antenna.

number of receiver antennas improves the performances. For example at SNR=5dB, perfect detection is achieved with a receiver composed of 4 antennas.

5.2. Performances of the HLRT classifier

In a non cooperative environment, the channel matrix **H** is unknown and the ALRT classifier is impractical. The HLRT classifier does not require this information. The figure 2 presents the performances of the HLRT classifier with respect to the signal to noise ratio. For $n_r = 2$ receiver antennas, the probability of correct detection is close to 0.98 at SNR=20dB whereas the ALRT achieves perfect detection at SNR=15dB with $n_r = 2$. Like the ALRT classifier, we can remark that increasing the number of receiver improves the probability of correct detection of the HLRT method. For $n_r = 3$ and $n_r = 4$ antennas, the probability is close to 1 at SNR=15dB and SNR=10dB respectively.

6. CONCLUSION

This paper described two new methods for the blind modulation recognition of MIMO communications. The first method, based on ALRT, is optimal but requires the knowledge of the channel matrix. This information is usually unknown in a non cooperative environment. To overcome this problem, we have proposed an alternative classifier. Under the assumption that the number of receiver antennas is greater than the number of transmitter antennas, the second classifier performs an ICA preprocessing to convert the MIMO communication into n_t SISO communications. Then an HLRT classifier is used to recognize individually the modulation of each SISO communication. Compared to the optimal performances obtained with ALRT, simulations show that the HLRT classifier performs well. Furthermore, the probability of correct detection of the two classifiers increases with respect to the number of receiver antennas. Future works will deal on the recognition of space time codes and OFDM modulations which can be used in MIMO communications.

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